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SERC DISCUSSION PAPER 201

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**Revised November 2016**  
**(Replaced July 2016 version)**

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# **The Geography of City Liveliness and Consumption: Evidence from Location-Based Big Data**

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**Revised November 2016**  
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**Abstract**

Understanding the complexity in the connection between city liveliness and spatial configurations for consumptive amenities has been an important but understudied research field in fast urbanising countries like China. This paper presents the first step towards filling this gap through location-based big data perspectives. City liveliness is measured by aggregated spacetime human activity intensities using mobile phone positioning data. Consumptive amenities are identified by point-of-interest data from Chinese Yelp website (dian ping). The results provide the insights into the geographic contextual uncertainties of consumptive amenities in shaping the rise and fall in the vibrancy of city liveliness.

Keywords: big data, local linear estimator, city liveliness, consumption, China  
JEL Classifications: C14; P25

*“Liveliness and variety attract more liveliness; deadness and monotony repel life.”—  
Jane Jacobs*

# 1 Introduction

Consumptive amenities have been and will remain as an essential component for the city liveliness. This is particularly the case in fast urbanizing countries where cities are much denser than developed countries. This paper explores whether the city liveliness has benefited from spatial configurations for consumptive amenities, and the spatial-temporal heterogeneity they introduce. “City liveliness” is a conceptually thought situation implied in Jacobs (1961, 1969). Following Jane Jacobs’ fundamental viewpoint, a small and growing body of literature uses big data visualization techniques to map and model human activity patterns based on mobile phone data on an hourly basis (see e.g Blondel et al., 2015; Tranos and Nijkamp, 2015; Louail et al., 2014; Jacobs-Crisioni et al., 2014). Studies of a particular mega-city in developed countries provide little basis, however, for assessing the connection between city liveliness and consumptive amenities into a context of spatial-temporal uncertainties in a developing country, a key focus of this study.

Our exploration is of interest for three reasons. First, from the early 1990s, China began to relax land use supply and migration restrictions in order to re-establish the land market and labor market systems in cities. After economic transitions in China over the past two decades, we see that the Chinese cities allocated diverse land uses to neighborhoods and building blocks in order to satisfy people’s needs for not just durable goods like housing, but also consumptive amenities such as restaurants, beauty shops and hair salons, Karaoke Television (KTV) pubs, shopping malls and local groceries that are provided mainly by the private sector. The evidence that urban amenities can be significantly capitalized into Beijing households’ willingness to pay for properties (Zheng and Kahn, 2008; Wu and Dong, 2014; Wu et al., 2015) allows us to assume that spatial configurations do matter in influencing people’s quality of life. To the extent that land use resources could have been better allocated at the local area level, understanding the connection between spatial configurations of consumptive amenities and city liveliness is an important geography and planning concern.

Second, with the increasing consumption in the Chinese mega-cities comes the need to manage spatial configurations for consumptive amenities. Schiff (2015) finds population density has a strong impact on the amount of non-tradable consumptive amenities(e.g restaurants) in US cities, and sheds lights on the role of Central Place Theory (Openshaw and Veneris, 2003) to play in influencing a city’s consumer product variety. Using food catering businesses data as a lens, Zheng et al. (2016) examines the impacts of rail transit improvements on neighbor-

hood catering businesses in Beijing and argues the importance of consumer amenities' role in influencing city liveliness. Our investigation about the implication of spatial configurations of consumptive amenities on city liveliness is immediately relevant to this line of research.

Third, there is little empirical evidence supporting the claim of the spatial-temporal uncertainties of the connection between consumption amenity configurations and human activity intensities. Whereas the distribution of consumptive amenities in a city is relatively stable during a short period of time, the distribution of human activity is far from static. With the help of ever-increasing public transport and private vehicles, residents in a city can move rapidly from one site to another. The fact that city liveliness is constantly changing across city and over time, and that consumptive amenities are static during short period of time, implies the way city liveliness and land use are connected is less likely to be an homogeneous process, especially when the time period is restricted to 24hrs. This not only calls for statistical techniques capable of dealing with spatial and temporal heterogeneity, but also requires fine scale big space-time data to facilitate estimation and inference. To this end, a spatially-temporally varying coefficient regression is developed, and when combined with newly emerged location based big data, helps to evaluate the geography of city liveliness within a large developing country context.

We extend the conclusions of the previous literature in two ways. First, we find evidence of the heterogeneous effects of consumptive amenities on human activity intensities and provide micro implications underlying the fundamental viewpoint of city liveliness. Second, our estimation results clarify the importance of considering the spatial dependence and temporal dependence simultaneously in the evaluation of the dynamics of city liveliness. Methodologically, our approach contributes to the literature dealing with the presence of spatial and temporal heterogeneity in uncertain geographical contexts (Kwan, 2012). To identify the spatial-temporal varying effects, we examine both time series and cross-sectional variation in our data and exploit semi-parametric specifications known as varying coefficient models (see e.g. Wu et al., 1998; Fan and Zhang, 1999, 2008). Varying coefficient models allow regression coefficient to vary with some covariates, eg. space and time, therefore provide the insights on heterogeneous dynamics of the spatial-temporal process. The principle of this modeling process is similar to that of Geographical and Temporal Weighted Regression (GTWR, Huang et al., 2010; Fotheringham et al., 2015). This paper develops a local linear estimator that improves upon the GTWR. Our estimator combines both local estimation and first-order Taylor approximation, which gauges the bias of borrowing local data. Recent simulation studies (e.g Bhattacharjee et al., 2016) suggest that local linear method possesses better statistical properties compared with local constant method such as GTWR. To our knowledge, this is a key methodological innovation to the existing literature in similar empirical settings.

The remainder of this paper is structured as follows. Section 2 illustrates the data and

context. Section 3 describes the methodology. Section 4 presents the results. Section 5 discusses the implication of this study. Section 6 concludes and points to future work.

## 2 Data and Context

### 2.1 Coding Mobile Phone Positioning Data

This paper extracts location-based big data from mobile phone positioning records for studying space-time city liveliness at micro levels:  $1km \times 1km$  grid unit. We utilize the mobile phone positioning data from the most popular location-based social network service (SNS) provider *Tencent*<sup>1</sup> in China. *Tencent* has complied various mobile phone-based social media applications (including QQ and WeChat services) that allows us to map the precise geographical locations of individual users based on their geographically position system (GPS) records. Based on the 2015 *Tencent* big data center’s report (<http://data.qq.com/>), there are approximately 450 million mobile phone positioning records generated by mobile phone users per day in Beijing (averaged 20 footprints per person per day), and these records can be accessed from *Tencent*’s mobile phone big data platform “*Easygo*”. From this big data platform, we have obtained the newly generated mobile phone-based locational activity per hour ( $\tau$ ) per 100 meter square grid unit over a 2-weeks life span (from 15 June 2015 to 28 June 2015) in Beijing metropolitan areas. These activity records were aggregated to the  $1km$  square grid unit levels so as to match with aggregated consumption amenity configuration data (see the next sub-section for detail).

To be a valid proxy for human activity intensity, the distribution of the mobile phone positioning data should be highly correlated with the actual distribution of population density. As a partial test for this, we have collected the contemporary population density distribution data at the 1 kilometer square unit level from the LandScan database<sup>2</sup>. The scatter plot (Figure 1a) shows that activity intensities from the mobile phone positioning data are good predictors of the population density distribution, with the correlation coefficient equal to 0.76 ( $p$ -value  $< 0.001$ ). We conduct a further comparison between positioning densities during 20 : 00 – 22 : 00 and the night light intensity levels<sup>3</sup>. Figure 1b shows a strong correlation (0.71) between the two variables. Empirical studies have shown that night light intensity levels can be reliable proxy indicators for reflecting the local socioeconomic activity (Henderson et al., 2012). These results suggest the representativeness of mobile phone positioning data as a sub-population sample with great spatial and temporal detail (Deville et al., 2014). When visualized, the

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<sup>1</sup>see <https://en.wikipedia.org/wiki/Tencent>

<sup>2</sup>The LandScan is the finest resolution global population distribution database designed by the Oak Ridge National Laboratory, US: <http://web.ornl.gov/sci/landscan/index.shtml>

<sup>3</sup>Data source: Visible Infrared Imaging Radiometer Suite (VIIRS)- <http://ngdc.noaa.gov/eog/viirs>



remarkable spatial details of mobile phone positioning data allow us to observe the presence of human activity at fine temporal and spatial scales in a Chinese mega-city (see Figure 2).

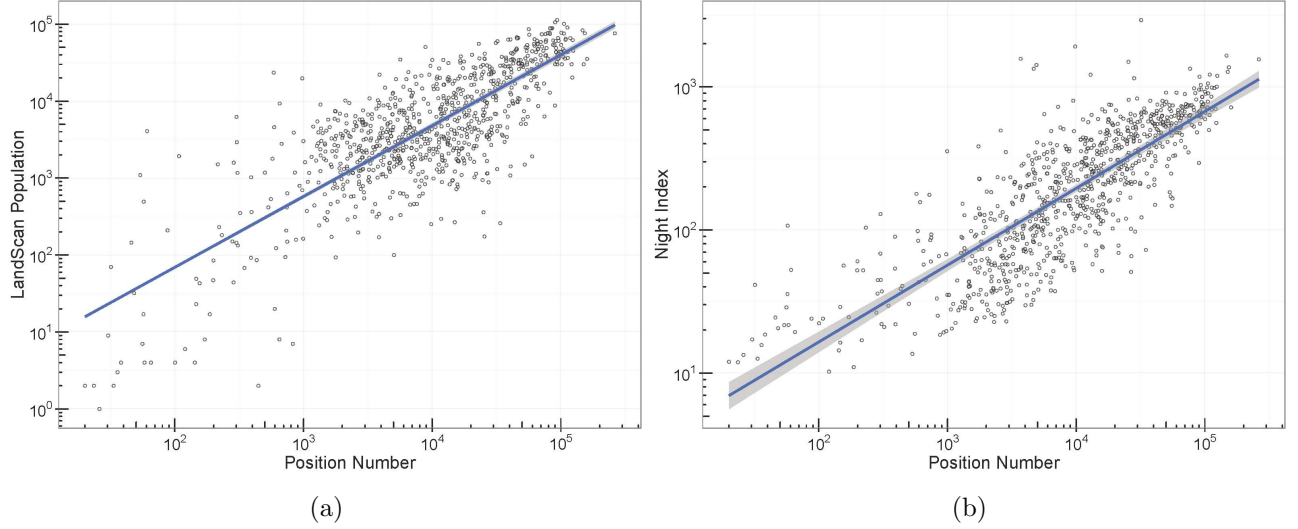


Figure 1: (a) Correlation between population distribution and activity distribution (correlation coefficient: 0.76;  $p$ -value < 0.001); (b) Correlation between night light intensity distribution and activity distribution (correlation coefficient: 0.71;  $p$ -value < 0.001)

Although recent studies suggest that human activity intensities derived from mobile phone data may not severely affect modeling exercises at the collective levels (Jacobs-Crisioni et al., 2014), there are several limitations underlying the mobile phone positioning data. The first limitation comes from the inherent data nature. The positioning data are recorded when people use specific applications (e.g. WeChat) in Global Positioning System (GPS)-enabled mobile phones. It is possible that some mobile phones do not have GPS functionality or the GPS function has been disabled. It is also possible that some mobile phone users have more activities recorded than others because they use mobile phones more frequently. Therefore, it is important to filter out such impact in the empirical analysis. For duplicate records from the same device, unique user identifiers are used to clean excessive data at each time period. For a rigorous assessment, we apply the whole sample rather than a sub-sample (e.g. a 1% limit of sampling tweets) provided by mobile phone positioning service companies so as to reduce the population bias.

As compared to traditional surveys, the second limitation is that mobile phone positioning records do not discern users' socioeconomic characteristics and types of activity at specific time and location. This is to say that, our data cannot deal with the "who is who" and "who is doing what" problems that may be associated with social mobility, capital and diversity (Agrawal et al., 2006; Saxenian and Sabel, 2008; Nathan, 2014; Nathan and Lee, 2013). For example, young people are more likely to use mobile phone services for business and leisure purposes than

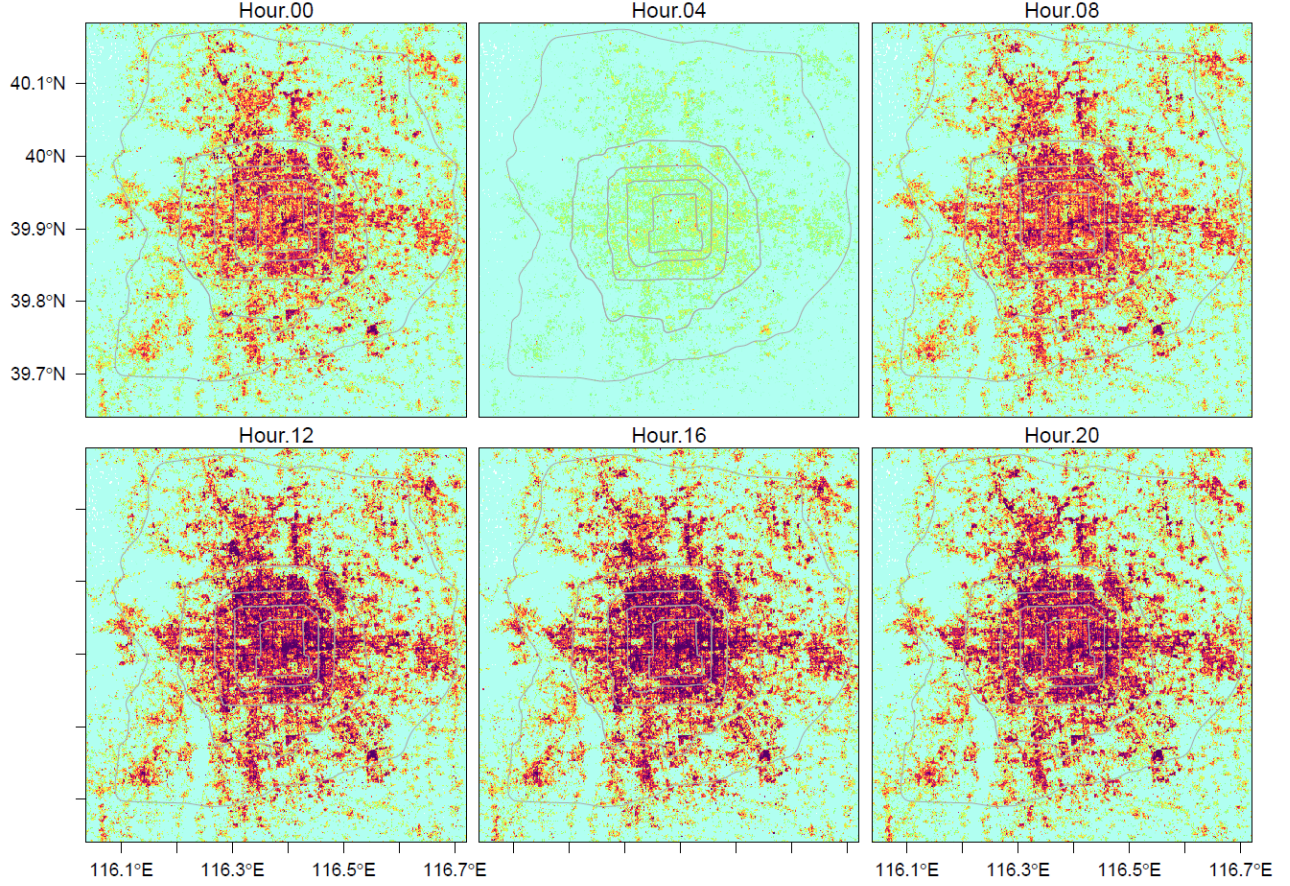


Figure 2: Spatio-temporal distribution of mobile phone positioning data

elderly people. In addition, the number and the demography of users may change over time and space. It is likely that workers in industrial areas switching on their phones during lunch break and students may switch off their smartphones during courses. It is also likely that when people are in work (e.g. during 8-12am in the working days), there are less mobile phone positioning data since they cannot chat much as in other activity. Further, people may be more likely to post their emotion and activities when they are relaxing at home or shopping malls than when they are working. We are not able to observe the diversified aspects of individual-level human behavior characteristics due to privacy data considerations. When longer-term data are available, future work could make use of the duration of activity and interact travel behavior information with personal characteristics to collaborate the robustness of our findings.

Despite of potential limitations, mobile phone positioning data are useful in several ways. First, unlike traditional survey and census information, which are limited both with respect to sample size, accuracy, cost and refreshing frequency, mobile positioning produces up-to-date, high-frequency data with little human effort. This feature not only enables researches based

on micro spatial and temporal scales (e.g. by hours, by weekdays and by weekends), but also offers much more details into the pattern of human activity, otherwise ignored in self-report data. Second, Tencent social media services have huge user basis in China. It is reported that in Q2 2015(sampling period), there are 600 million monthly active user<sup>4</sup>, close to half of the total population in China. The ratio is expected to be much higher in a metropolitan city like Beijing, where mobile services and Internet are cheap and readily available. We acknowledge that if the trajectory flows or footprints data are available rather than just the number of positions, it would be more worthwhile to show how people flow within or between the central city, inner suburb areas, and outer suburb areas. If the relationship of spatial configurations with the trajectory flows could be identified from the mobile phone positioning data, there could be stronger evidence of Jane Jacobs’s implications about the city liveliness. Our study is not able to test this conjecture given the current data limitations.

## 2.2 Coding point of interest data

Our spatial context is geographically-coded by detailed maps. The spatial configurations of consumptive amenities are treated as the POIs. These POIs are extracted from the Chinese Yelp and mapping website ([www.dianping.com](http://www.dianping.com)). Approximately 345,500 POIs have been identified, from which we can base our measurement. Consumptive amenities are measured by the number of restaurants, shopping malls, stores as well as leisure-related facilities in a given areal unit. We recognise that land uses for consumptive amenities essentially offer informal places for social interactions and transporting ideas between people. These ideas and information are transported by people as they engage in social media settings. But it is hard to find the data regarding the internal layouts of consumptive amenities that may facilitate social media usages such as wifi access. The differences in consumptive amenities would potentially produce divergent intensities of mobile phone positioning records and social engagement opportunities at micro levels. In addition to the location information, we have gathered the median monthly website "hits" numbers for inclusive consumptive amenities reported by the Chinese yelp website in a given areal unit. The availability of this information enables us to assess the quality aspects of the vibrancy of consumption activities at the areal level. The model and estimator developed in the subsequent section will provide the methodology to uncover the non-stationarity of spatial-temporal process and study the connection between city liveliness and consumptive amenities, conditional upon locational-specific characteristics such as the number of subway stations at the local area level and distance to the central business district (CBD). Based on the POI data, our model specifications also control for residential amenities (Housing) and

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<sup>4</sup><https://www.statista.com/statistics/255778/number-of-active-wechat-messenger-accounts/>



other amenities at a given grid unit level. For each POI, its location coordinate information was verified by the Google map. The richness of spatial details in this dataset thus enables us to visualise the spatial configurations of key observable amenities at the micro level (Figure 3).

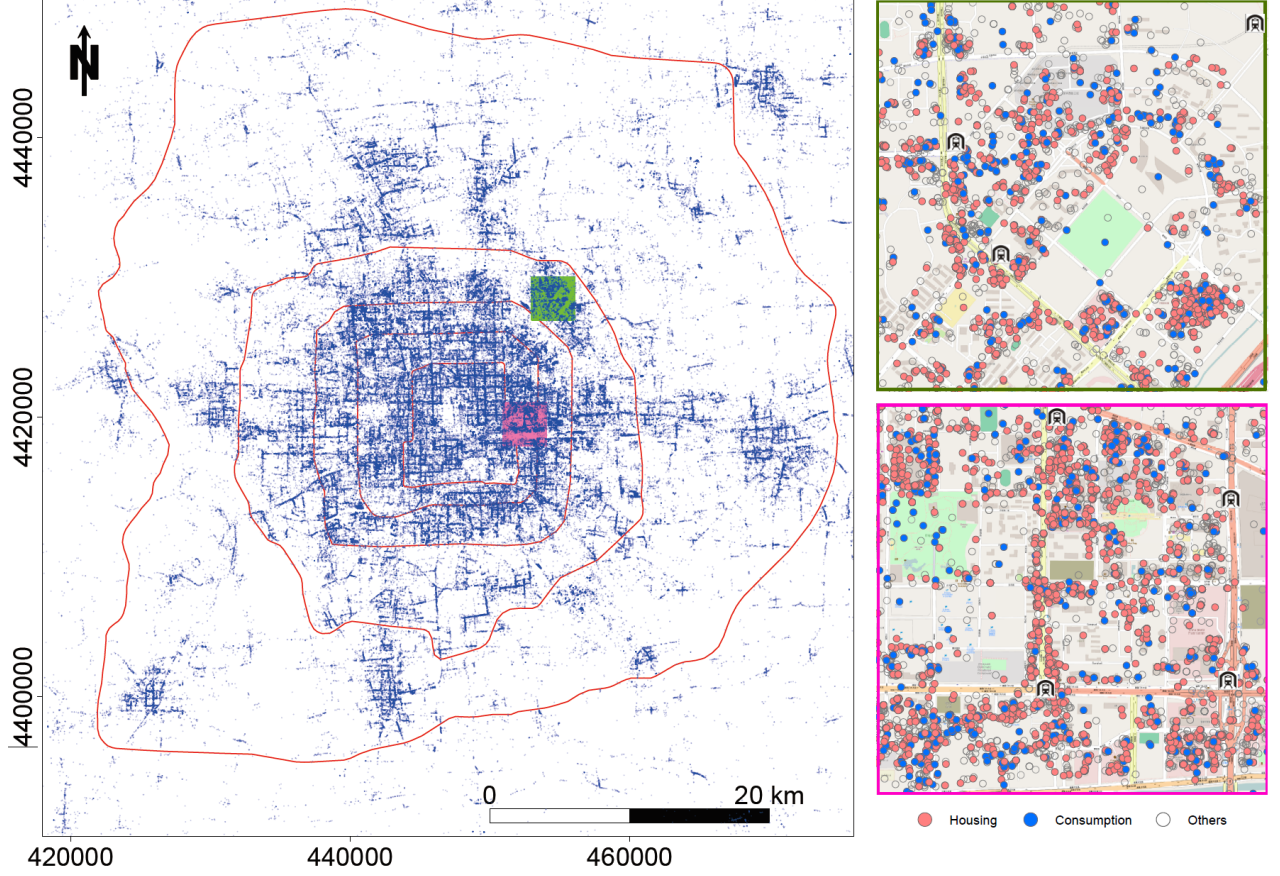


Figure 3: Distribution of spatial configurations using web-based Chinese yelp mapping data. Notes: The left panel shows the general distribution of spatial configurations in the whole city. The right panel graphs zoom into the two typical areal units (Wangjing in the upper right graph and Guomao in the lower right graph). Different color ramps indicate different land use types

### 3 Econometric Model

Following Glaeser et al. (2001), we argue that a place is likely to be vibrant with dense consumptive amenities that can retain diverse human activity in the urban space. These are not easy to transport and are thus localized goods.

We consider two model specifications in this paper, the first which is the non-spatial traditional panel regression model,

$$\ln y_{it} = \ln C_{it}\delta + \mathbf{z}_{it}^T\boldsymbol{\theta} + \varepsilon_{it}, \quad i = 1, \dots, 3480, t = 1, \dots, 24 \quad (1)$$

and the second is a spatially-temporally varying coefficient regression model which allows for heterogeneous effect,

$$\ln y_{it} = \ln C_{it} \beta(a_i, b_i, \tau_t) + \mathbf{z}_{it}^T \boldsymbol{\theta} + \varepsilon_{it}, \quad i = 1, \dots, 3480, t = 1, \dots, 24 \quad (2)$$

The dependent variable  $\ln y$  is the human activity intensity level, measured by logarithm of average mobile phone positioning records per grid unit  $i$  at hour  $\tau = 1, \dots, 24$  during weekdays and weekends respectively. Therefore, temporal difference between weekdays and weekends are separately modeled. Grid units are aggregated at  $1km \times 1km$  geographic scale. Variation in mobile phone positioning data across space and time will serve as a proxy for the aggregated city liveliness at fine geographical scales.

For independent variables (regressors), key variable of interest is the logarithm of “number of consumptive amenities per grid unit”,  $\ln C_{it}$ . Besides, we include in both specifications a number of control variables  $\mathbf{z}_{it}^T = (z_{it})$  such as road density levels, the number of subway stations, housing and other amenities at the grid unit level that are of great relevance to mixed land uses (Anas and Moses, 1978), as well as location specific dummies and temporal dummies (Table 1) to account for unobserved factors.  $\boldsymbol{\theta}$  is a vector of unknown coefficients.

Two specifications differ mainly in the coefficient of consumptive amenities. Whereas the panel regression assumes homogeneous effect of consumption on human activity, the varying coefficient model assumes non-stationary coefficient. Specifically, coefficient  $\beta(a_i, b_i, \tau_t)$  is assumed to be an unknown function of latitude( $a_i$ ), longitude ( $b_i$ ) and time ( $\tau_t$ ). As the coefficient value is allowed to vary with both location and time, we explicitly model the spatial and temporal heterogeneity.

We hypothesize that spatial configurations for consumptive amenities in a given areal unit play important roles in influencing changes in human activity patterns. But we recognize that temporary changes on localized land uses such as the opening show of living performance in newly-opened theaters, the closing of a shopping mall, or the relocation of a nice Chinese restaurant are not included in these data. This mechanism may possibly affect human activity intensities at particular time slots and particular areas of the city.

### 3.1 Local Linear Estimator

We are mainly interested in estimating  $\gamma$  and  $\beta(\cdot)$  function, the linkage between consumptive amenities and mobile phone activity. Estimation of the first specification is straightforward, whereas the second one requires elaboration. To achieve identification, we assume varying coefficients  $\beta(a, b, \tau)$  is a smooth function defined on a compact set  $S \times I$ , ( $S$  is the spatial domain and  $I$  is the temporal domain). To estimate the coefficient function, a generic point estimator

Table 1: Descriptive statistics of key variables

Variable Name	Definition	Mean	SD	Min	Max
Activity intensity at weekday(ywd)	Average mobile phone positioning data per grid unit at weekday (in 1000 people)	5.415	10.075	0.004	225.924
Activity intensity at weekend(ywn)	Average mobile phone positioning data per grid unit at weekend,(in 1000 people)	5.322	9.459	0.004	218.127
Housing amenities (H)	Number of POIs related to residential complex compounds per grid unit	1.372	3.209	0	32
Consumptive amenities(C)	Number of POIs related to entertainment and leisure services per grid unit	75.762	174.954	0	2177
Other amenities	Number of POIs that do not fall in the categories of Housing and Consumptive amenities per grid unit	18.149	41.359	0	546
Stations	Number of subway stations per grid unit	0.121	0.833	0	42
Road Density	Road lengths per grid unit (in kilometers)	5.711	4.425	0	23.281
Distance to CBD	Straightline distance from each grid unit to the CBD (in kilometers)	22.441	9.000	0	44.926
Median of Hits	Median Monthly website “hits” numbers (in 1000) for inclusive consumptive amenities per grid unit	0.0206	1.970	0	70.442

is required for an arbitrary location and time,  $(a, b, \tau)$ . A fundamental challenge in this process lies in the fact that functions are intrinsically infinite dimensional as opposed to finite data available. Therefore smoothing is normally required to obtain meaningful estimates. We employ local estimation which is based on the idea that that near-by  $\beta$  values are similar, under the smoothness assumption. Therefore, close-by data are ‘borrowed’ to estimate coefficient value at any location/time.

To illustrate the method, we pick an arbitrary location  $(a, b)$  and time  $\tau$ , two bandwidths,  $h_1$  and  $h_2$ , which specify the sizes of close-by spatial neighbourhoods and time neighbourhoods. Two bandwidths are needed as space and time are not measured with the same unit. For data  $(a_i, b_i, \tau_t)$  ( $i = 1, \dots, N, t = 1, \dots, T$ ) such that  $\|(a_i, b_i) - (a, b)\| \leq h_1$  and  $|\tau_t - \tau| \leq h_2$ , we have the following Taylor approximation, which stipulates the relationship between  $(a_i, b_i, \tau_t)$  (Point B in Figure 4) and  $(a, b, \tau)$  (Point A in Figure 4) on a smooth varying coefficient  $\beta$  (blue curve in Figure 4),

$$\begin{aligned}
\beta(a_i, b_i, \tau_t) &\approx \beta(a, b, \tau) + \frac{\partial \beta(a, b, \tau)}{\partial a}(a_i - a) + \frac{\partial \beta(a, b, \tau)}{\partial b}(b_i - b) + \frac{\partial \beta(a, b, \tau)}{\partial \tau}(\tau_t - \tau) \\
&:= \beta(a, b, \tau) + \beta^{(a)}(a_i - a) + \beta^{(b)}(b_i - b) + \beta^{(\tau)}(\tau_t - \tau)
\end{aligned} \tag{3}$$

The formula is known as the first-order Taylor approximation through which data coefficient values  $\beta(a_i, b_i, \tau_t)$  and arbitrary coefficient value  $\beta(a, b, \tau)$  are connected. The approximation

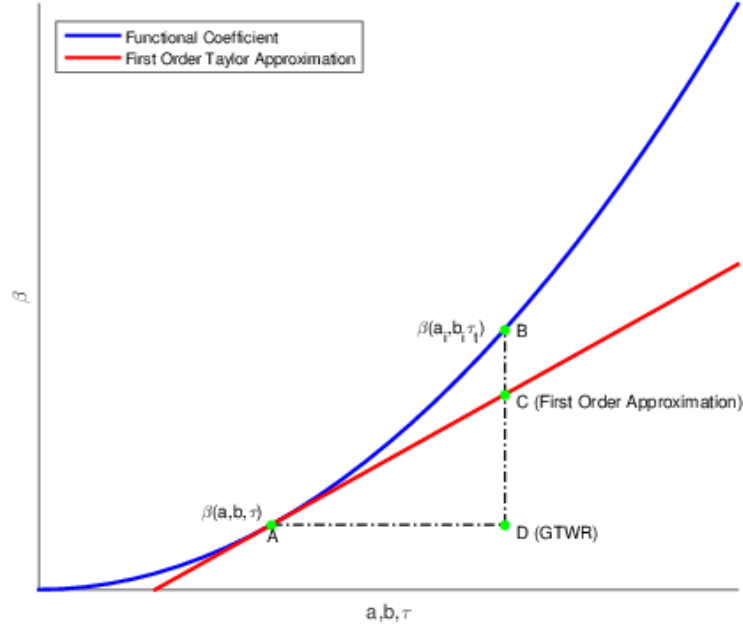


Figure 4: Geometry of GTWR and First Order Taylor Approximation

error is the size of the line segment  $BC$  (see Figure 4), which is not captured by first-order derivatives. The error can be made arbitrarily small by adding higher order terms.

GTWR is actually a special case of the Taylor approximation,

$$\beta(a_i, b_i, \tau_t) \approx \beta(a, b, \tau) \quad (4)$$

where only the first term is picked up and higher order (including first order) terms are abandoned. The approximation error of GTWR is shown in the Figure 4 as the  $BD$  segment. Evidently,  $BC \leq BD$  under any circumstances, indicating first order approximation brings less approximation bias compared with that of GTWR. To improve the efficiency of GTWR, we suggest to include  $\frac{\partial \beta(a, b, \tau)}{\partial a}(a_i - a) + \frac{\partial \beta(a, b, \tau)}{\partial b}(b_i - b) + \frac{\partial \beta(a, b, \tau)}{\partial \tau}(\tau_t - \tau)$  as control in the regression. As first order derivatives  $\frac{\partial \beta(a, b, \tau)}{\partial a}$ ,  $\frac{\partial \beta(a, b, \tau)}{\partial b}$ ,  $\frac{\partial \beta(a, b, \tau)}{\partial \tau}$  are unknown, they will be jointly estimated.

Compared with GTWR, our estimator captures some of the bias from using local data and provide more accurate approximation. Bhattacharjee et al. (2016) recently tests the finite sample performance of local constant and local linear estimators in a series of Monte Carlo simulations. The results suggest that local linear estimators with first order as control will outperform local constant type (e.g GWR/GTWR) estimators. If the underlying coefficient function is smooth, the bias controlled by the first order terms will be non-trivial. If the underlying function is not very smooth, or the bandwidths are large, first order approximation

may capture less bias. Then higher order terms (second, third) could be added as control. However, encompassing higher order terms will significantly increase the number of higher order derivatives to be estimated, which we shall not pursue here.

To estimate the whole varying  $\beta$  curve and non-varying coefficient  $\theta$ , we employ the following ‘profile strategy’. In the first step, non-varying coefficients  $\theta$  are treated as if they are known parameters, and then define

$$y_{it}^* = \ln y_{it} - \mathbf{z}_{it}^T \theta \quad (5)$$

In doing so, we profile out the interference of non-varying coefficient and regression (2) is left with varying coefficient only. For an arbitrary location and time vector,  $(a, b, \tau)$ , two bandwidths  $h_1$  and  $h_2$ , plug in the first order approximation equation (3) and 5 for  $\beta$  into regression (2),

$$\begin{aligned} y_{it}^* &= \ln C_{it} \beta(a_i, b_i, \tau_t) + \varepsilon_{it} \\ &\approx \ln C_{it} \beta(a, b, \tau) + \beta^{(a)} \ln C_{it} (a_i - a) + \beta^{(b)} \ln C_{it} (b_i - b) + \beta^{(\tau)} \ln C_{it} (\tau_t - \tau) + \varepsilon_{it} \end{aligned} \quad (6)$$

The approximation works well if  $(a_i, b_i, \tau_t)$  is close to  $(a, b, \tau)$  and is less accurate if they are further apart (See Figure 5  $B'C' \leq BC$ ). Therefore, observations should be properly weighted according to the distances between samples and target location-time (See Figure 5).

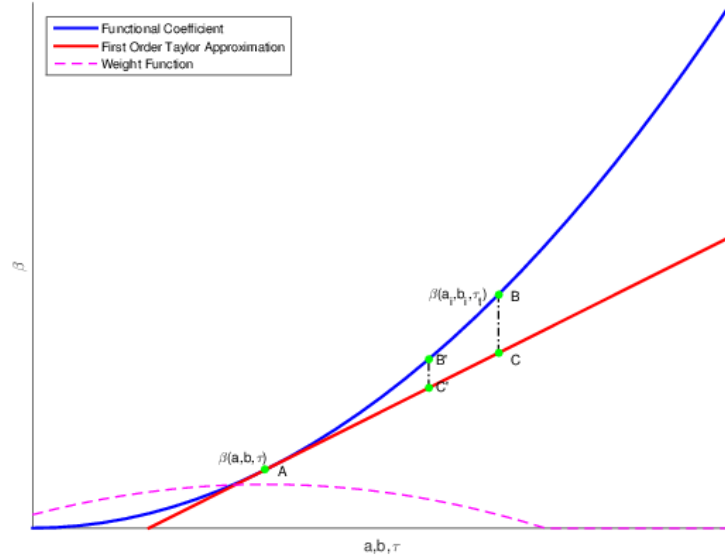


Figure 5: Weighting Scheme



We define the weight function as the product of spatial kernel and temporal kernel weight-

$$K(\|(a_i, b_i) - (a, b)\|/h_1) \times K(|\tau_t - \tau|/h_2) \quad (7)$$

where  $K(\cdot)$  is a kernel function (e.g Epanechnikov kernel:  $K(u) = 0.75(1 - u^2)\mathbb{1}_{|u| \leq 1}$ )

Next, we combine equation (6) and weighting scheme (7) to obtain a weighted objective function,

$$\sum_{i=1}^N \sum_{t=1}^T \left\{ y_{it}^* - \ln C_{it} \beta(a, b, \tau) - \beta^{(a)} \ln C_{it}(a_i - a) - \beta^{(b)} \ln C_{it}(b_i - b) - \beta^{(\tau)} \ln C_{it}(\tau_t - \tau) \right\}^2 \times K(\|(a_i, b_i) - (a, b)\|/h_1) \times K(|\tau_t - \tau|/h_2) \quad (8)$$

Optimizing the objective function (8) leads to a weighted least square (WLS) type estimator, defined as

$$[\hat{\beta}(a, b, \tau), \hat{\beta}^{(a)}(a, b, \tau), \hat{\beta}^{(b)}(a, b, \tau), \hat{\beta}^{(\tau)}(a, b, \tau)]^T = (\mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Q}_{a,b,\tau})^{-1} \mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Y}^* \quad (9)$$

where  $\mathcal{W}_{a,b,\tau} = \text{diag} \left( K(\frac{\|(a_1, b_1) - (a, b)\|}{h_1}) \times K(\frac{|\tau_1 - \tau|}{h_2}), \dots, K(\frac{\|(a_N, b_N) - (a, b)\|}{h_1}) \times K(\frac{|\tau_T - \tau|}{h_2}) \right)$ ,  $\mathcal{Y}^* = (y_{1,1}^*, \dots, y_{NT}^*)^T$ ,  $\mathcal{Q}_{a,b,\tau} = (\ln C_{it}, \ln C_{it}(a_i - a), \ln C_{it}(b_i - b), \ln C_{it}(\tau_t - \tau))_{i=1, \dots, N; t=1, \dots, T}$

As we are mainly interested in coefficient value itself rather than first order partial derivatives, we take the first element the vector (9). The estimator is modified as follows,

$$\begin{aligned} \hat{\beta}(a, b, \tau)^T &= a_{1,4}^T (\mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Q}_{a,b,\tau})^{-1} \mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Y}^* \\ &= a_{1,4}^T (\mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Q}_{a,b,\tau})^{-1} \mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} (\mathcal{Y} - \mathbf{Z}\boldsymbol{\theta}) \end{aligned} \quad (10)$$

where  $a_{1,4}^T = (1, 0, 0, 0)$ ,  $\mathcal{Y} = (\ln y_{11}, \dots, \ln y_{NT})^T$ ,  $\mathbf{Z} = (\mathbf{z}_{11}, \dots, \mathbf{z}_{NT})^T$

The proposed estimator (10) is not feasible as it involves unknown non-varying coefficients  $\boldsymbol{\theta}$  in  $\mathcal{Y}^*$ . To estimate the non-varying coefficients, we plug (10) back into the regression (2),

$$\ln y_{it} = \ln C_{it} \hat{\beta}(a_i, b_i, \tau_t) + \mathbf{z}_{it}^T \boldsymbol{\theta} + \varepsilon_{it}$$

As  $\hat{\beta}_1(a_i, b_i, \tau_t)$  only involves data and coefficients  $\boldsymbol{\theta}$ , it can be shown that the above equation is then reduced to the following matrix form regression (see Fan and Zhang (2008)),

$$(I_{NT} - \mathbf{S}) \mathbf{Z} \mathcal{Y} = (I_{NT} - \mathbf{S}) \mathbf{Z} \boldsymbol{\theta} + \boldsymbol{\varepsilon} \quad (11)$$

where  $I_{NT}$  is a  $NT$  identity matrix and  $\mathbf{S}$  is defined as,

$$\mathbf{S} = ([\mathbf{z}_{it}^T, 0, 0, 0](\mathcal{Q}'_{a_i, b_i, \tau_t} \mathcal{W}_{a_i, b_i, \tau_t} \mathcal{Q}_{a_i, b_i, \tau_t})^{-1} \mathcal{Q}'_{a_i, b_i, \tau_t} \mathcal{W}_{a_i, b_i, \tau_t})_{i=1, \dots, N; t=1, \dots, T} \quad (12)$$

In regression (11), the varying coefficient has been ‘profiled out’, therefore estimation of  $\boldsymbol{\theta}$  is easily estimated by least square.

$$\hat{\boldsymbol{\theta}} = [\mathbf{Z}^T (I_{NT} - \mathbf{S})^T (I_{NT} - \mathbf{S}) \mathbf{Z}]^{-1} \mathbf{Z}^T (I_{NT} - \mathbf{S})^T (I_{NT} - \mathbf{S}) \mathbf{Z} \mathbf{Y} \quad (13)$$

Once  $\hat{\boldsymbol{\theta}}$  become available, we insert the estimator into  $\hat{\beta}$  to obtain a feasible curve estimate.

$$\hat{\beta}_{feasible}(a, b, \tau)^T = a_{1,4}^T (\mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} \mathcal{Q}_{a,b,\tau})^{-1} \mathcal{Q}'_{a,b,\tau} \mathcal{W}_{a,b,\tau} (\mathbf{Y} - \mathbf{Z} \hat{\boldsymbol{\theta}}) \quad (14)$$

### 3.2 Bandwidth Selection

In order to implement the estimator, the sizes of the bandwidths  $h_1, h_2$  need to be decided. A smaller  $h$  leads to less bias, but also creates bigger variance. A bigger  $h$  on the other hand, provides more stable estimates, but also generates more bias. Suitable  $h_1, h_2$  will strike a balance between bias and variance(MSE). In this paper we follow the statistical literature and choose bandwidths by cross-validation (Fan and Zhang, 2008), picking  $h_1, h_2$  which minimize the sum of leave-one-out squared errors,

$$\hat{h}_1, \hat{h}_2 = \arg \min_{h_1, h_2} \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T [Y_{it} - \hat{Y}_{-it}(h_1, h_2)]^2 \quad (15)$$

where  $\hat{Y}_{-it}$  is the predicted value for  $i, t$  without using  $(i, t)th$  datum to estimate the model.

Other methods are also available to pick optimal bandwidth. For example, instead of leaving one out, we could leave  $k$  observations out, where  $k > 1$ . However, leave- $k$ -out would significantly increase the computational cost when the data size is big, as it involves  $\frac{(NT)!}{k!(NT-k)!}$  different combinations for each bandwidth iteration.

### 3.3 Finite sample performance- a Monte Carlo simulation

To test the finite sample performance of the estimator we proposed in this paper and compare it with GTWR, we perform a Monte Carlo simulation experiment. We specify a spatial domain  $S$  to be  $[0, 1] \times [0, 1]$  rectangle and time range  $I$  to be  $[0, 2]$ . The data generating process is defined as follows. A single regressor  $x_{it}$  is independently drawn from  $N(3, 1)$ . Dependent

variable  $y_{it}$  is generated by the following regression specifications,

$$y_{it} = x_{it} \cdot \beta_1(a_i, b_i, \tau_t) + \varepsilon_{it} \quad (\text{Design 1})$$

$$y_{it} = x_{it} \cdot \beta_2(a_i, b_i) + \varepsilon_{it} \quad (\text{Design 2})$$

$$y_{it} = x_{it} \cdot \beta_3(\tau_t) + \varepsilon_{it} \quad (\text{Design 3})$$

$$i = 1, \dots, N, t = 1, \dots, T$$

where  $\beta_1(a_i, b_i, \tau_t) = a_i^2 + b_i^2 + \cos \tau_t$ ,  $\beta_2(a_i, b_i) = a_i^2 + b_i^2$ ,  $\beta_3(\tau_t) = \cos \tau_t$ , and  $\varepsilon_{i,t}$  is an i.i.d draw from  $N(0, 0.5^2)$ .  $N$  coordinates and  $T$  time points are randomly selected from the discretized space  $S$  and time range  $I^5$ .

We consider the following sample size  $N = 50, T = 10$ ;  $N = 100, T = 20$ ;  $N = 200, T = 50$ , which correspond to small, medium and large sample designs. For each sample size, the coefficients are estimated by both GTWR(outlined in Fotheringham et al., 2015) and our estimator for  $R = 1000$  replications. To evaluate the performance of each estimator, we compute the mean summed squared error (MSSE) for each case (Ruppert et al., 2003), defined as

$$MSSE(\hat{\beta}_k) = \frac{1}{R \cdot N \cdot T} \sum_{j=1}^R \sum_{i=1}^N \sum_{t=1}^T [\hat{\beta}_k^{(j)}(a_i, b_i, \tau_t) - \beta_k(a_i, b_i, \tau_t)]^2, \quad k = 1, 2, 3 \quad (16)$$

Note that when both the replication number and sample size is large, MSSE will be made arbitrarily close to the integrated mean square error (IMSE),

$$IMSE(\hat{\beta}_k) = \mathbb{E} \int_a \int_b \int_I [\hat{\beta}_k(a, b, \tau) - \beta_k(a, b, \tau)]^2 da db d\tau \quad (17)$$

which is the  $L_2$  measure of the squared error between an functional estimate and its true value.

Table 2: Monte-Carlo Results

Estimator	N	T	MSSE( $\beta_1$ )	MSSE( $\beta_2$ )	MSSE( $\beta_3$ )
Local Linear Estimator	50	10	0.02038*	0.0185*	0.00049*
	100	20	0.0076*	0.0053*	0.000101*
	200	50	0.0028*	0.002*	0.00006*
GTWR	50	10	0.0259	0.0224	0.0034
	100	20	0.0096	0.0067	0.00034
	200	50	0.0038	0.0025	0.000074

Replication:1000. \* indicates smaller MSSE ceteris paribus

<sup>5</sup> $S$  is discretized into  $1000 \times 1000$  grid and  $I$  is discretized into  $1 \times 2000$  intervals.

Monte Carlo results in Table 2 show that our estimator significantly outperforms GTWR in terms of MSSE under different scenarios. This gives us more confidence about the reliability of our estimation strategy. Overall, the model setup outlined above has several features. First, the model is based on more flexible assumptions, which reduces potential specification bias under multivariate linear regression with fixed coefficients. Second, compared with fully nonparametric specification, our model could incorporate some prior information (such as linearity), and therefore circumvent the so-called “curse of dimensionality” in the presence of many observable variables (Härdle et al., 2012). Third, spatially and (or) temporally varying coefficients are closely linked to the notion of spatial and temporal heterogeneity.

## 4 Results

### 4.1 Non-Spatial Model Estimates

Table (3) reports the average elasticity of spatial configurations for consumptive amenities based on conventional panel estimators. Columns (1) (3) (5) of Table 3 show the results using the weekday sub-sample, whereas Columns (2) (4) (6) of Table 3 show the results using the weekend sub-sample. For both sub-samples, we use the aggregated space-time human activity at the  $1km$  grid unit on an hourly basis as the dependent variable. As mentioned in the previous section, fixed effect and first difference estimators are incapable of estimating model with time-invariant dependent variables, and between estimator, random effect estimator will report exact the same estimates as pooled regression. Therefore, the regression table only reports one set of estimates based of pooled regression, along with cluster robust error.

Model specifications in columns (1) (2) report estimates of consumptive amenities and monthly median hit numbers, after controlling for key observable locational-specific characteristics including transport, road density, distance to CBD, POI-based residential and other amenity configurations. For weekday sub-samples, we find that the elasticity for consumptive amenities (consumption elasticity) with respect to human activity is 0.493, and the result is robust when using the weekend sub-samples. This suggests that 1% change of the number of consumptive amenities is associated with approximately 0.49% change in human activity intensity levels. In addition, there is evidence of significantly positive effects of web-based hit numbers on human activity intensity levels. It should be noted that our data cannot capture the heterogeneity nature within the consumptive amenities. These estimates, therefore, only capture the average effects of consumptive amenities. Further, the results reveal highly divergent roles of POI-based residential and other amenities in attracting human activity. For example, the negative coefficients associated with the POI-based residential amenities suggest that the

Table 3: The relationship between human activity intensity and spatial configurations

	(1) lnYd	(2) lnYn	(3) lnYd	(4) lnYn	(5) lnYd	(6) lnYn
Log Consumptive Amenities	0.493*** (46.72)	0.497*** (49.80)	0.487*** (46.85)	0.491*** (49.83)	0.483*** (47.74)	0.487*** (50.86)
Median of Hits	0.0135*** (43.14)	0.0136*** (34.41)	0.0129*** (41.49)	0.0130*** (32.86)	0.0137*** (43.53)	0.0139*** (35.52)
Log Residential Amenities	-0.147*** (-13.19)	-0.152*** (-13.47)	-0.145*** (-13.19)	-0.149*** (-13.41)	-0.0866*** (-10.21)	-0.0865*** (-10.13)
Log Other Amenities	0.0986*** (27.50)	0.0942*** (21.78)	0.141*** (38.04)	0.137*** (28.79)	0.168*** (40.77)	0.166*** (30.68)
Transport (No. of Stations)	1.535*** (24.67)	1.543*** (22.36)	1.573*** (24.69)	1.583*** (22.50)	1.050*** (28.01)	1.080*** (22.69)
Road Density	0.0222*** (22.62)	0.0188*** (27.24)	0.0308*** (24.01)	0.0277*** (28.82)	0.0323*** (24.13)	0.0293*** (28.49)
Distance to CBD	-0.0519*** (-46.78)	-0.0527*** (-57.01)	-0.0584*** (-45.03)	-0.0595*** (-54.75)	-0.0582*** (-45.05)	-0.0593*** (-54.71)
Central City			-0.827*** (-26.31)	-0.834*** (-32.05)	1.291*** (26.15)	1.314*** (31.20)
Inner Suburb			-0.368*** (-21.25)	-0.383*** (-26.76)	0.628*** (19.09)	0.682*** (20.38)
Log Consumption* Transport					1.337*** (11.21)	1.159*** (11.07)
Log Consumption* Inner City					-0.378*** (-30.35)	-0.385*** (-37.62)
Log Consumption* Inner Suburb					-0.227*** (-20.90)	-0.243*** (-22.91)
Constant	-0.197 (-0.92)	-0.153 (-0.73)	-0.0743 (-0.34)	-0.0264 (-0.12)	-0.128 (-0.59)	-0.0825 (-0.39)
N	69168	69168	69168	69168	69168	69168

*t* statistics in parentheses(Cluster Robust Error)

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

presence of "gated" residential complex communities might discourage, though negligibly, a small share of human activity, though we cannot pin down the precise mechanism. Note that residential complex (ju zhu she qu) projects in Beijing are mostly gated communities. However, it is possible that some residential complex projects may still be traditional Danwei communities with intensive social engagement and job-housing relationship (Chai, 1996; Wang and Chai, 2009). We also find that better transport accessibility, identified by number of subway stations and road density, is associated with larger mobile phone-based human activity intensities. For example, the point estimate associated with the number of subway stations using weekday subsample is 1.535. This indicates that ceteris paribus, one extra subway station is associated with 0.1535% - 0.1543% increase in the human activity intensity levels. Distance to CBD estimates are  $-0.0519$  (weekday) and  $-0.0527$  (weekend), both statistically significant.

Columns (3) and (4) include additional area specific dummies into the regression specifications based on weekday and weekend samples respectively. We find that the all the key coefficients are elasticity estimates are robust to the inclusion of additional controls. For area specific dummies, we divide the whole metropolitan areas into central Beijing, inner suburb, and outer suburb areas. Outer suburb areas are deemed as the benchmark. The estimates in columns (5) (6) also confirm the intuition that outer suburb areas attract less human activity as compared with the central city and inner suburb areas in Beijing.

Estimates from specifications in columns (5) and (6) shed lights on the interaction effects between spatial configurations for consumptive amenities and transport accessibility, as well as area-specific dummies. These specifications partly account for potential spatial heterogeneity in the elasticities of consumptive amenities relative to human activity intensity levels. For interaction term with transport amenities, we find that better access to subway stations is associated with larger positive effects of spatial configuration of consumptive amenities on human activity. For area dummy interactions, our results reveal differential elasticities of land uses for housing and consumption with respect to human activity across central Beijing, inner suburb and outer suburb areas. In particular, the estimates suggest that the outer suburb (benchmark) has the highest elasticity in comparison to inner suburb and central city areas. The estimates in column (5) and (6) suggests that the estimates coefficients of consumptive amenities in column (1)-(4) might be misleading, as it only reflects the average association whereas the relationship is highly heterogeneous across urban and suburban areas.

In the results that are not reported, our model specifications include the land-use mixing entropy index as measured by colocations of densities of various amenity uses within a given grid unit but did not find useful results. As suggested by recent studies (Manaugh and Kreider, 2013; Jacobs-Crisioni et al., 2014), aggregated land use mix index cannot observe micro land use colocations. We therefore focus on the presence of densities of land uses for consumptive amenities, rather than the aggregated land use mixing levels. Future work on spatial dependencies between colocations of land use mix and human activity is needed.

## 4.2 Spatially-Temporally Varying Estimates

The panel estimates indicate there exists large variation in the elasticity of spatial configurations of consumptive amenities. Including interaction terms help to discover some of the heterogeneity, but only to a very coarse scale. Besides, the panel estimates do not inform us how the elasticities evolve continuously over 24 hours.

To gain a better understanding of how the connection between consumptive amenity configurations and human activity interact varies at different times and locations, we now turn to

spatial-temporal varying estimates based on the methods proposed in section 3. As the varying coefficient estimates are defined on three dimensional domains, it is difficult to visualize the regression results. To deal with this challenge, we use two strategies. First, we examine the temporal variation dimension for key estimated coefficients of consumption elasticities  $\hat{\beta}(a, b, \tau)$ . In doing so we generate purely temporally varying coefficient estimates by averaging cross-sectional units over space. Second, we consider the spatial variation dimension by averaging  $\hat{\beta}(a, b, \tau_t)$ , for all  $t$  hours.

Figure 6 shows the temporal variation in the consumption elasticities averaged over the whole spatial domain. The blue lines represent the estimated elasticities using the weekday sub-sample and red lines show the estimated elasticities using the weekend sub-sample. Graphs of Figure 6 show the average elasticity of consumptive amenity over the whole city, central city, inner suburb and outer suburb, respectively. The graphical evidence is consistent with the panels estimates in column (3) (4) (5) (6), and suggests substantial heterogeneity over the city region. In general, graphs of Figure 6 reveal similar temporal patterns. In early morning, the coefficients have a tendency to drop and during the day, the elasticities climb back rapidly. This partially coincides with Beijing residents' sleeping, working and living patterns, as well as the opening hours of shopping and other consumption services in Beijing. Meantime, we find that the temporal variation of consumption elasticities varies greatly across central city, inner suburb, outer suburb areas.

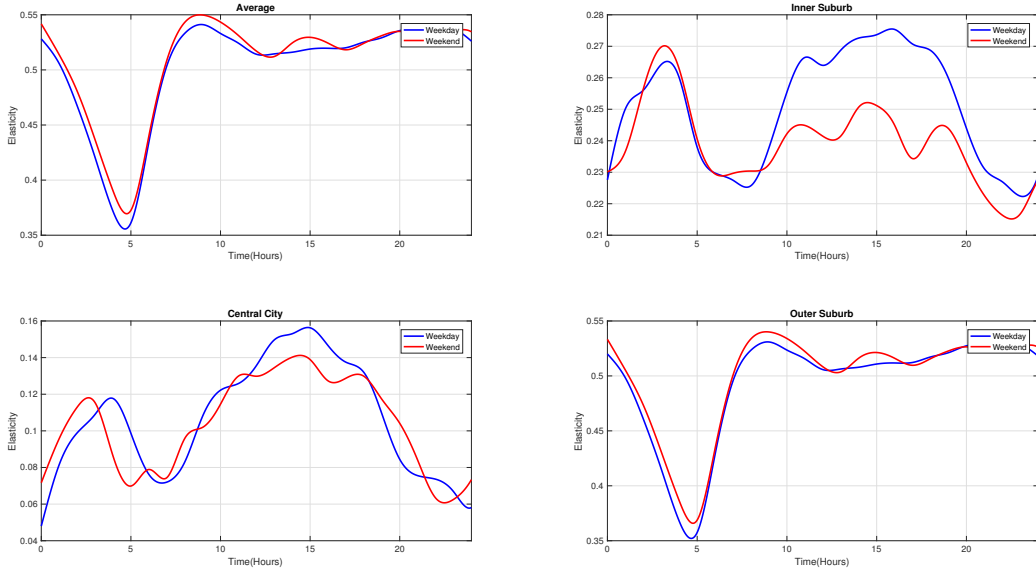


Figure 6: Temporal variation between urban areas and suburban areas at 1km scale

Figure 7 plots the distribution of log-log scattered points between estimated coefficients of

consumptive amenities and distance to the CBD. The smoothed solid line shows the distributional trend and the grey areas surrounding the solid line represent 95% confidence intervals. At the aggregated level, we find that there is a general increasing trend of estimated coefficients of consumptive amenities with respect to the distance to the CBD. At the individual grid unit level, we find strong evidence of the substantial spatial heterogeneity in the impact of spatial configuration of consumptive amenities on human activity intensity when moving from city center to outer suburb areas. Overall the headline implication of these findings confirms that spatial configurations of consumptive amenities have the significantly heterogeneity impacts on human activity intensities over time and space. We interpret these heterogeneous effects as a multiplier mechanism that can influence the city liveliness. When one is reading the results, it is important to keep in mind that although we know the rise and decline of human activity at an hourly basis, it is difficult to examine who are mostly active in specific hours or at specific places. Testing for these mechanisms is beyond the scope of this paper. That said, tracking human activity intensity from aggregated mobile phone positioning data cannot identify people's socio-demographic characteristics and what are people actually doing in different locations over time. This may undermine the interpretation of the results at the individual level.

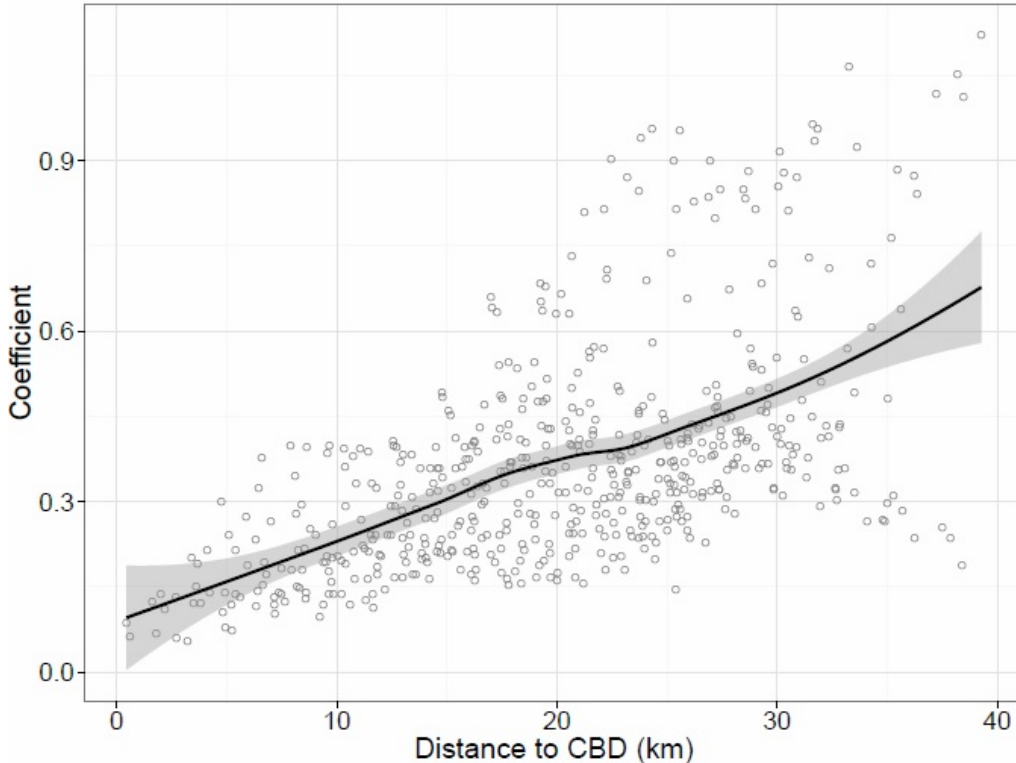


Figure 7: Coefficient against distance to CBD



## 5 Implications of this study

In urban contexts, the ever-expanding big data has fascinated geographers and planners alike (Graham and Shelton, 2013; Elwood and Leszczynski, 2013; Batty, 2013; Goodchild, 2013; Wu et al., 2016). Large scale point-of-interest (POI) data extracted from social media platforms represent micro land uses or amenity locations (e.g., a restaurant, a karaoke bar, or a school) that are of relevance to the interaction between people and places (Yoshida et al., 2010; McKenzie et al., 2014). With the ever-widening usage of location-based social media services on smart mobile phones, the inclusion of precise spatial-temporal dimension information enables the interface between the cyberspace of mobile phone usages and the geographic space of human activity locations (Deville et al., 2014). This makes mobile phone positioning data a reliable proxy for measuring city liveliness through tracking human activity intensities over time and space (Yuan and Raubal, 2012). Existing research, on the other hand, examines human activity intensities using mobile phone data in cities from western developed countries (e.g. see Ratti et al., 2006; Licoppe et al., 2008; Reades et al., 2009; Tranos and Nijkamp, 2015; Jacobs-Crisioni et al., 2014), or examines local land uses without using the detailed point of interest (POI) data as units of observations. The estimated results of the relationship between land uses and mobile phone usages from highly urbanized cities of western developed countries are obviously not relevant to Chinese cities with much denser population.

The contribution of spatial configurations of consumptive amenities to the city liveliness is substantial. To place these estimates in urban contexts it is useful to quantify the elasticities of consumptive amenities with respect to city liveliness based upon the spatial and temporal dependence evaluation. Land development on consumptive amenities through catering and leisure businesses might retain human activity. For example, consumptive amenities provide various private goods for serving city consumers which benefit the liveliness of urban and suburban areas depending on the timing and locations. Human activities that are located in commuter towns such as Tiantongyuan, Huilongguan, Fangshan, Yizhuang without good access to job opportunities have experienced a sharp variation of consumption elasticities in the morning peak hours and evening peak hours. In general, consumptive amenities contribute to the human activity levels mainly between 10:00 and 22:00 hours, resembling common Beijingers' liveliness patterns. Given a range of compositions of consumptive amenities at areal unit levels, we can nevertheless conclude that the average net value of a particular consumptive amenity type is of great importance to the city liveliness. This warrants further studies. Our findings provide the complementary evidence on the existing literature if one acknowledges the capitalization of consumption facilities to real estate markets (Zheng and Kahn, 2013) and the gentrification of public investments in new subway lines to specific retail businesses in Chinese

cities (Zheng et al., 2016).

A further implication points out the possibility that spatial configurations for consumptive amenities can generate observable effects on influencing city liveliness dynamics in excess of property prices. This suggests that substantial changes in human activity intensities are likely to promote incentives for further commercial development at particular locations. Given the short-time period (e.g. 2 weeks) in our study, spatial configurations of consumptive amenities are not likely to be evolved with changes in human activity distribution over space and time. A typical case in point is that even if such changes in human activity intensities were predicted to be forthcoming, existing spatial amenity configurations would be likely to retain their patterns at least in the short-run. Thus the reverse causality problem may not be as serious as it seems.

The disproportionate variation of elasticities of spatial configurations of consumptive amenities to city liveliness has several profound implications from political economy perspectives. First, the rise and decline of levels of human activity identified by mobile phone positioning big data could have ramifications for public investments. For example, neighborhoods with low human activity levels may be treated as depressed areas for gentrification through government investments in physical and social infrastructure projects such as subway stations, city expressways, urban village renewals and affordable housing provisions. In at least one scenario this channel has been sufficient to guide government investments to influence the spatial-temporal liveliness of human activity.

Second, it is not clear to what extent land use supply policy effectively serves as a substantial catalyst to promote the spatial-temporal liveliness of human activity in cities. To gain financial revenues through land auction sales (Zheng and Kahn, 2008), local governments have given great emphasis in allocating lands for commercial and residential property development. China's unique political structure allows city governments to support land development efficiently (Zheng and Kahn, 2008; Wu and Dong, 2014; Wu et al., 2015). The political economy of selling land parcels for development may skew the distributional consequence of city liveliness in that land bid prices do not capitalize different amenity values according to whether a place has higher or lower human activity intensities. This has serious consequences for the willingness of property developers to allocate additional spaces for opening affiliated consumption facilities such as supermarkets since these private goods are essential to facilitate people's social engagement activity within and between vibrant neighborhoods. Benefits of spatial configurations of consumptive amenities for attracting human activity might be sufficiently high to motivate private developers to manipulate development patterns so as to maximize road frontage for commercial and retail businesses. These development patterns are understandable since profit-maximizing developers have incentives to maximize the sale and rental value of land development. On the flip side, geographical concentrations of consumptive amenities

might lead to traffic congestion, noise, crime and other disamenities even if government investments in infrastructure have been allocated to mitigate these concerns. Countering these undesirable consequences may entail substantial urban management costs to sustain the city liveliness through rearranging land use configurations—costs that developers will not care about but mayors will do. This is likely to shape the suboptimal city liveliness patterns in Beijing for decades to come.

## 6 Conclusion

The provision of consumptive amenities has emerged as an important way of re-orientating the city liveliness in fast urbanizing countries. This paper looks at the role of consumptive amenities on city liveliness in Beijing, using a new panel of mobile phone positioning data and a unique amenity dataset based on point-of-interest (POI) Chinese Yelp information. We use a localized spatial-temporal econometric design that combines both spatial and temporal heterogeneous effects to uncover several distinctive complexities of the city liveliness and shed lights on potential “city liveliness-consumption” connections in a Chinese mega-city. Our work is the first of this type of applications to explore this connection outside the US and European countries.

Our analysis is complicated by the tendency for the simultaneous determination of spatial dependence and temporal dependence in geographically-coded mobile phone positioning data and by the likely importance of spatial-temporal heterogeneity in the effects of spatial configurations of consumptive amenities on city liveliness. To estimate a spatial-temporally varying coefficient model, conventional GTWR methods are popular, but found to be deficient in controlling the bias and variance of the estimated coefficients, leading to less reliable inference. Borrowing ideas from the statistical varying coefficient literature, we propose a new estimator that combines both local estimation and first-order Taylor approximation. In comparison to traditional spatial-temporal modeling approaches, our estimator adjusts possible bias from using local data and improves the accuracy of estimation and statistical inference. Our estimator is useful in spatial-temporal analysis where heterogeneous effects are of interest and serves as an improvement of the GTWR.

Turning back to our case application, our estimates of the elasticity of city liveliness with respect to consumptive amenities vary greatly at each individual location during a 24 hours life span. We discover significant across-location variation in the estimated elasticities over time, which reveal varying “liveliness premium” associated with urban and suburban areas in Beijing. This would be a partial reflection of the fundamental viewpoint of city liveliness, suggested by Jacobs (1961, 1969), where spatial configurations for consumptive amenities are connected with

human activity intensities at a nonlinear manner.

Our findings provide the insights for other developing countries planning to sustain the city liveliness. An attractive mix of consumptive amenities can affect dense and diverse human activity patterns. These consumptive amenities are likely to be key determinants of a city's gain in productivity and social capitals. These conditions are likely to be held in the European and US cities. Mayors in Chinese cities have strong political power in land resource allocations for consumptive amenities such as shopping malls and industrial business parks (Zheng et al., 2015). Future studies are encouraged to collaborate the importance of the co-location of different types of consumptive and productive amenities in driving the city liveliness and productivity.

There are at least several caveats to the interpretation of the results. First, tracking the human activity through mobile phone positioning data cannot fully reflect human capital and productivity in cities, which are more important determinants of a city's liveliness in history. Second, experimenting with big data presents a number of empirical challenges: our big data approaches have restricted us to use a fuzzy identification of the connection between city liveliness and consumptive amenities. This brings areas for future causal evaluation. Location-based big data with individual socio-economic characteristics would allow the identification of consumers' information to parallel empirical work on Glaeser et al. (2001)'s consumer city theory and explore the roles of consumers at specific hours when they are most active and in specific locations where they are most productive.

## References

- Agrawal, Ajay, Iain Cockburn, and John McHale (2006), “Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships.” *Journal of Economic Geography*, 6, 571–591.
- Anas, Alex and Leon N Moses (1978), *Transportation and land use in the mature metropolis*. Lexington Books Lexington Mass. United States 1977.
- Batty, Michael (2013), “Big data, smart cities and city planning.” *Dialogues in Human Geography*, 3, 274–279.
- Bhattacharjee, Arnab, Taps Maiti, Mark Wang, and Ping Shou Zhong (2016), “Spatially varying regression over irregularly shaped regions: Application to a hedonic house price model.” *Manuscript*.
- Blondel, Vincent D, Adeline Decuyper, and Gautier Krings (2015), “A survey of results on mobile phone datasets analysis.” *EPJ Data Science*, 4, 1–55.
- Chai, Y. (1996), “Danwei-centered activity space in chinese cities-a case study of lanzhou[in chinese].” *Geography Research*, 15, 30–38.
- Deville, Pierre, Catherine Linard, Samuel Martin, Marius Gilbert, Forrest R Stevens, Andrea E Gaughan, Vincent D Blondel, and Andrew J Tatem (2014), “Dynamic population mapping using mobile phone data.” *Proceedings of the National Academy of Sciences*, 111, 15888–15893.
- Elwood, Sarah and Agnieszka Leszczynski (2013), “New spatial media, new knowledge politics.” *Transactions of the Institute of British Geographers*, 38, 544–559.
- Fan, Jianqing and Wenyang Zhang (1999), “Statistical estimation in varying coefficient models.” *Annals of Statistics*, 1491–1518.
- Fan, Jianqing and Wenyang Zhang (2008), “Statistical methods with varying coefficient models.” *Statistics and its Interface*, 1, 179.
- Fotheringham, A Stewart, Ricardo Crespo, and Jing Yao (2015), “Geographical and temporal weighted regression (gtwr).” *Geographical Analysis*, 47, 431–452.
- Glaeser, Edward L, Jed Kolko, and Albert Saiz (2001), “Consumer city.” *Journal of economic geography*, 1, 27–50.

- Goodchild, Michael F (2013), “The quality of big (geo) data.” *Dialogues in Human Geography*, 3, 280–284.
- Graham, Mark and Taylor Shelton (2013), “Geography and the future of big data, big data and the future of geography.” *Dialogues in Human Geography*, 3, 255–261.
- Härdle, Wolfgang Karl, Marlene Müller, Stefan Sperlich, and Axel Werwatz (2012), *Nonparametric and semiparametric models*. Springer Science & Business Media.
- Henderson, J Vernon, Adam Storeygard, and David N Weil (2012), “Measuring economic growth from outer space.” *American Economic Review*, 102, 994–1028.
- Huang, Bo, Bo Wu, and Michael Barry (2010), “Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices.” *International Journal of Geographical Information Science*, 24, 383–401.
- Jacobs, Jane (1961), *The death and life of great American cities*. New York: Random House.
- Jacobs, Jane (1969), *The economy of cities*. New York: Random House.
- Jacobs-Crisioni, Chris, Piet Rietveld, Eric Koomen, and Emmanouil Tranos (2014), “Evaluating the impact of land-use density and mix on spatiotemporal urban activity patterns: an exploratory study using mobile phone data.” *Environment and Planning A*, 46, 2769–2785.
- Kwan, Mei-Po (2012), “The uncertain geographic context problem.” *Annals of the Association of American Geographers*, 102, 958–968.
- Licoppe, Christian, Dana Diminescu, Zbigniew Smoreda, and Cezary Ziemlicki (2008), “Using mobile phone geolocalisation for socio-geographical analysis of co-ordination, urban mobilities, and social integration patterns.” *Tijdschrift voor economische en sociale geografie*, 99, 584–601.
- Louail, Thomas, Maxime Lenormand, Oliva G Cantu Ros, Miguel Picornell, Ricardo Herranz, Enrique Frias-Martinez, José J Ramasco, and Marc Barthelemy (2014), “From mobile phone data to the spatial structure of cities.” *Scientific reports*, 4.
- Manaugh, Kevin and Tyler Kreider (2013), “What is mixed use? presenting an interaction method for measuring land use mix.” *Journal of Transport and Land Use*, 6, 63–72.
- McKenzie, Grant, Krzysztof Janowicz, Song Gao, Jiue-An Yang, and Yingjie Hu (2014), “Poi pulse: A multi-granular, semantic signatures-based information observatory for the interactive visualization of big geosocial data.” *Cartographica*, 50, 71–85.

- Nathan, Max (2014), “Same difference? minority ethnic inventors, diversity and innovation in the uk.” *Journal of Economic Geography*, 1bu006.
- Nathan, Max and Neil Lee (2013), “Cultural diversity, innovation, and entrepreneurship: Firm-level evidence from london.” *Economic Geography*, 89, 367–394.
- Openshaw, Stan and Yannis Veneris (2003), “Numerical experiments with central place theory and spatial interaction modelling.” *Environment and Planning A*, 35, 1389–1403.
- Ratti, Carlo, Dennis Frenchman, Riccardo Maria Pulselli, and Sarah Williams (2006), “Mobile landscapes: using location data from cell phones for urban analysis.” *Environment and Planning B: Planning and Design*, 33, 727–748.
- Reades, Jonathan, Francesco Calabrese, and Carlo Ratti (2009), “Eigenplaces: analysing cities using the space–time structure of the mobile phone network.” *Environment and Planning B: Planning and Design*, 36, 824–836.
- Ruppert, David, Matt P Wand, and Raymond J Carroll (2003), *Semiparametric regression*. 12, Cambridge university press.
- Saxenian, AnnaLee and Charles Sabel (2008), “Roepke lecture in economic geography venture capital in the periphery: the new argonauts, global search, and local institution building.” *Economic Geography*, 84, 379–394.
- Schiff, Nathan (2015), “Cities and product variety: evidence from restaurants.” *Journal of Economic Geography*, 15, 1085–1123.
- Tranos, Emmanouil and Peter Nijkamp (2015), “Mobile phone usage in complex urban systems: a space–time, aggregated human activity study.” *Journal of Geographical Systems*, 17, 157–185.
- Wang, Donggen and Yanwei Chai (2009), “The jobs–housing relationship and commuting in beijing, china: the legacy of danwei.” *Journal of Transport Geography*, 17, 30–38.
- Wu, Colin O, Chin-Tsang Chiang, and Donald R Hoover (1998), “Asymptotic confidence regions for kernel smoothing of a varying-coefficient model with longitudinal data.” *Journal of the American statistical Association*, 93, 1388–1402.
- Wu, Wenjie and Guanpeng Dong (2014), “Valuing the green amenities in a spatial context.” *Journal of Regional Science*, 54, 569–585.

- Wu, Wenjie, Guanpeng Dong, and Wenzhong Zhang (2015), “The puzzling heterogeneity of amenity capitalization effects on land markets.” *Papers in Regional Science*.
- Wu, Wenjie, Jianghao Wang, and Tianshi Dai (2016), “The geography of cultural ties and human mobility: Big data in urban contexts.” *Annals of the American Association of Geographers*, 106, 612–630.
- Yoshida, Daisuke, Xianfeng Song, and Venkatesh Raghavan (2010), “Development of track log and point of interest management system using free and open source software.” *Applied Geomatics*, 2, 123–135.
- Yuan, Yihong and Martin Raubal (2012), “Extracting dynamic urban mobility patterns from mobile phone data.” In *Geographic information science*, 354–367, Springer.
- Zheng, Siqi, Xiaoke Hu, Jianghao Wang, and Rui Wang (2016), “Subways near the subway: Rail transit and neighborhood catering businesses in beijing.” *Transport Policy*.
- Zheng, Siqi and Matthew E Kahn (2008), “Land and residential property markets in a booming economy: New evidence from beijing.” *Journal of Urban Economics*, 63, 743–757.
- Zheng, Siqi and Matthew E Kahn (2013), “Does government investment in local public goods spur gentrification? evidence from beijing.” *Real Estate Economics*, 41, 1–28.
- Zheng, Siqi, Weizeng Sun, Jianfeng Wu, and Matthew E Kahn (2015), “The birth of edge cities in china: Measuring the spillover effects of industrial parks.” *National Bureau of Economic Research Working Paper No. 21378*.





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